Chapter

Volatility Effects of the Global Oil Price on Stock Price in Nigeria: Evidence from Linear and Non-Linear GARCH

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Abstract

This present study examines the volatility effects of the oil price on the stock price returns in Nigeria from the period of 2000M(12) to 2020M(4) on a monthly data using both standard GARCH and non-linear GARCH models. The motivation for the present study is the recent fall in the global oil price of Brent Crude to US$15.25 per barrel due to the outbreak of the Corona Virus (COVID-19). Consequentially, the Nigerian stock market (NSE) responded with a fall of 4172 point or by a fall of 15.53%. After establishing the presence of heteroscedasticity through the ARCH test and volatility clustering through the returns, the outcome of the study contributes to knowledge by providing financial information and signals to investors about the best GARCH model response to proactively and successfully use to model global oil price shocks so as to reduce financial risk in Nigeria's stock market.

Keywords: oil price volatility, stock market returns, linear and non-linear GARCH models, Nigeria

1. Introduction

Oil price changes have been known to have direct impact on stock market returns depending whether the affected country is an oil-exporting or importing country [1–4]. The effects are usually different across countries. For oil-importing countries, the increase in oil price usually leads to fall in stock market returns, while the increase may not necessarily reduce the stock market returns in oil exporting countries. The experience in Nigeria has also been a significant one, not only as an oil exporting county but also as an oil-dependent one. Nigeria depends on oil exports such that it represents 90% of foreign exchange earnings and greatly determines the execution of the country's yearly budget [5]. The transmission of oil price volatility to the stock market returns stems from two channels. The first channel may be limited to investment in oil companies and this can occur when there is fall in equity investment of oil companies in oil-exporting countries due to fall in the global oil price. The second channel is broader and affects all sectors of the economy. It can come from foreign portfolio investors moving their financial assets from an oil dependent economy due to fall in the global oil price. This is usually due to the investors' perception that they may suffer huge financial loss if their investments are not quickly moved. Therefore, the stock market is so sensitive and important that it serves as long term funds for investment, businesses, financial institutions, private and the public. It is such that investors are much more concerned about the volatility of their returns in terms of gain and losses.

Apart from the theoretical and the empirical support, the stock market returns have been further verified to respond to the global oil price during the period of study in Nigeria (**Figure 1**). Therefore, since oil price volatility has been the major source of uncertainty in stock market returns especially in an oil-dependent economy like the sample country, it is then imperative to study their relationships. The unpredictability in the movement of oil price and its correlation with stock price returns have made it imperative for financial investors, practitioners, risk managers and policy makers to be interested in appropriate volatility model that best predicts minimum variance of the stock returns. Some previous studies in Nigeria have examined volatility using GARCH models. Salisu [6] examined comparative performance of both Brent oil and Western Texas Intermediate (WTI) oil across subsamples in Nigeria using GARCH models and found that bad news in the oil market increased oil price than good news. Najjar [7] applied ARCH, GARCH and EGARCH to Amman stock exchange in Jordan to study the return volatility of the market and found GARCH model to explain the extent of volatility clustering and leptokurtosis in the stock market. Uyaebo et al. [8] used non-linear GARCH models on the all share index of six selected stock market of Nigeria, Kenya, Germany, South Africa, China and United States for the period of February 2000 to February 2013. The study found volatility to be faster and persist in Nigeria and Kenya only. The study by [9] also investigated volatility of banks' equity returns on weekly basis for six commercial banks using GARCH models from January 2010 to June 2016. The study found EGARCH and CGARCH as the best volatility model in Nigeria. This present paper is different from the previous papers and contributed to the literature in two ways. First, we used different error distributions in the estimation of the standard GARCH and the non-linear GARCH models which previous studies have failed to take into consideration. Second, this study extends into the period of the COVID-19, the first quarter of the year 2020, which is another period of global shocks to both the oil market and the stock market.

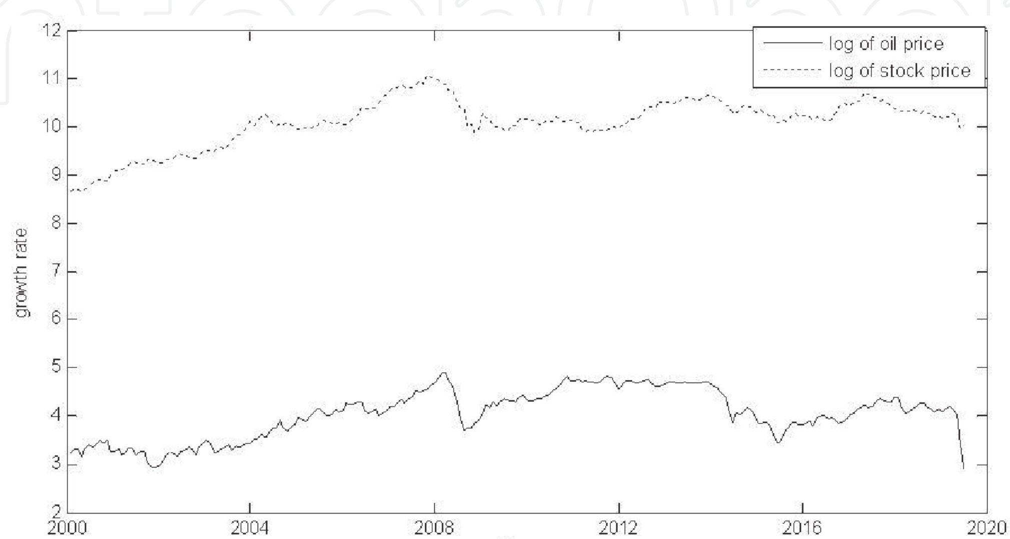


Figure 1.
The movement of change in oil price and stock price over the study period.

2. Literature review

The literature review on the relationship between stock price and oil price volatility in this study is done along the type of generalized autoregressive conditional heteroscedasticity GARCH type adopted. Hammoudeh and Aleisa [10] studied the causal relationship between oil price and stock price and found causality emanating from the variables for Saudi Arabia. Also, Bashar [11] examined the effects of oil price on stock market of five GCC countries such as Bahrain, Kuwait, Oman, Saudi Arabia and Abu Dhabi with daily data from the period of 25th May, 2001 to 24th May, 2005. The study found a bidirectional respond between Saudi stock market and the oil price shocks in vector autoregression (VAR) analysis.

In another paper for GCC, [12] investigated the volatility and channel of shocks among US equity market, global oil market and the equity market of Saudi Arabia, Kuwait and Bahrain. Of all the three equity markets, only Saudi Arabia equity market had significant volatility spillover to the oil market with the multivariate (GARCH) with BEKK. Arouri et al. [13] applied a generalized VAR-GARCH approach to examine the volatility channel between oil and stock market of Europe and the US. After analyzing the optimal weights and hedge ratio for oil-stock portfolio, the study found different volatility spillover for the selected European and the US stock market with VAR-GARCH being the best asset-hedging model. Khalfao et al. [14] investigated the relationship between West Texas Intermediate (WTI) crude oil market and the stock market of G-7 countries using wavelet-based MGARCH method. The mean and the variance of the study showed significant volatility spillover between the G-7 stock market returns and the oil market. Bouri [15] also applied ARMAX-GARCH to model and predict stock market returns of investors of oil-exporting countries like Lebanon and Jordan. The selected MENA countries are Morocco and Tunisia. The study found volatility spillover from the oil market to only Jordan stock market. In another paper, [16] examined directional connectedness between oil market and equity by applying implied volatility indices for 11 stock markets for the period of 2008–2015. A one-way transmission was found from oil market to equity market. Khamis et al. [17] used causality and multivariate regression method with daily data from the year 2012 to 2015 to examine the response of Saudi Arabia stock market to oil price fluctuation at the sectoral level. The finding is that Saudi Arabia stock market showed different to oil market. In recent paper, [18] examined the connection between oil price and stock market for net oil-exporting and net oil-importing countries such as Russia, Canada, United States and Japan using cointegration analysis. The study found significant and positive connection only between Russian stock market and oil price for the study period of 2007–2016.

3. Source of data and variable definition

The data used for this study were monthly data from the period of January 2000 to April 2020. The data were sourced from the Statistical Bulletin [19] published by Central bank of Nigeria (CBN) and the United State (US) Energy Information Administration [20]. Specifically, the Brent oil price was sourced from the US Energy Information Administration while the equity All Share Price Index (ASPI) was sourced from CBN and augmented with the monthly online data of Nigerian Stock Exchange [21]. The reason for the choice of equity stock price over bond is due to its high risk, high volatility and its sensitivity to market events and financial news which normally affect its returns. Bonds, on the other hand, offer lower returns with fixed interest and less sensitive to financial news and risk. Also, the choice of Brent spot oil price as against West Texas Intermediate (WTI) oil price is because the Nigeria's oil export is usually measured and priced in Brent oil market while the WTI is a bench mark for North American market. The stock price is measured as the monthly equity investment of ASPI in Naira on Nigerian Stock exchange while the Brent oil price is the monthly global oil price in US dollar per barrel (pbl) in the international oil market. The returns of both stock price and oil price were generated through the log of difference ($d\log X$) of the series which can be mathematically written as: $d\log X = \log X - \log X(-1)$.

3.1 Descriptive statistics

The statistical distributions of the 252 monthly observations of stock price and oil price with their returns used in this study are presented in **Table 1**. The average monthly observation of the oil price returns is -0.0013%, which implies that there were losses and low returns on oil revenue during the period of study. The high difference between the maximum oil price of $US132.72 and the minimum value of $US18.38 confirms the high volatile nature of the oil price. For the stock price returns, the minimum value is negative with a value of -0.3659. This implies that the stock price returns is less volatile than the oil price returns with minimum value of -0.55%. Although, there is also a large difference between the maximum value of the stock price with N65652.38 in billion and the minimum values of N5892.8 billion. The variability is just lower compared to that of the oil price. The standard deviation, skewness and kurtosis greater than zero imply that distribution is not normally distributed except for both returns that are close to zero and being normal. The positive skewness of 0.39% and 0.55% for oil price and stock price imply that their distributions are skewed to the right. On the other hand, the negative skewness of -1.75% and -0.47% for oil price returns and stock price returns imply that their distributions are skewed to the left. Furthermore, the kurtosis of oil price with value of 2.09% and the stock price with value 3.51 imply normal distribution because the values are less than 3. However for the returns, the kurtosis value of 9.08 and 7.71% for both oil price returns and stock price returns denote leptokurtic characteristic. Lastly, the null hypothesis for Jarque-Bera is that the data is normally distributed, however, with the probability value of 0.00 less than 0.05% in **Table 1**, then the null hypothesis is rejected and the alternative hypothesis that the data are

Statistics	Oil price	Oil price returns	Stock price	Stock price returns
Mean	64.35	−0.0013	27315.4	0.0056
Median	61.96	0.0164	26011.64	0.0024
Maximum	132.72	0.1979	65652.38	0.3235
Minimum	18.38	−0.5548	5892.8	−0.3659
Std-dev	29.91	0.1035	11756.38	0.0708
Skewness	0.39	−1.7543	0.55	−0.4734
Kurtosis	2.09	9.0837	3.51	7.71
Jarque-Bera	14.69	499.37	14.74	233.47
Prob.	0.00	0.00	0.00	0.00
Observation	252	252	252	252

Table 1.
Descriptive analysis.

Augmented Dickey Fuller test			Phillips-Perron test		
Variables	**Levels**	**Status**	**Variables**	**Levels**	**Status**
Oil price returns	−10.0663	I(0)	Oil price returns	−10.015	I(0)
Stock price returns	−13.5579	I(0)	Stock price returns	−13.5579	I(0)
The critical values are −3.4573, −2.8733 and −2.5731 for 1, 5, and 10%, respectively.					

Table 2.
Results of the unit root tests.

F-Statistics	7.9138	Prob. F(1,241)	0.00
Obs*R-squared	7.7257	Prob. Chi-Square(1)	0.00
Scale explained SS	5854	Prob. Chi-Square(1)	0.00

Table 3.
Breusch-pagan-Godfrey test.

not normally distributed is accepted. It is evident that the statistical properties of the variables used in this study can be described as fat tailed, leptokurtic and deviated from normal distribution which is typical of financial time series, risks and returns.

3.2 Preliminary test

The first exercise after the descriptive analysis is to verify the stationary properties of the variables used in the analysis and then test for the ARCH effect on the variables. Once the variables are stationary and ARCH effect is present, then we can proceed to estimate the GARCH models. The Augmented Dickey Fuller [22] and the Philips-Perron [23] tests were conducted and the results shown in **Table 2**. The unit root results show that both oil price returns and stock price returns are stationary at levels. The stationarity of the returns of the variable of interest is one of the conditions for carrying out the GARCH process.

The final preliminary test is to test for ARCH effects using Breusch-Pagan-Godfrey method of Engle [24] to verify the presence of heteroscedasticity and proceed to the GARCH process. The heteroscedasticity test presented in **Table 3** shows the presence of heteroscedasticity, which means that the variance is not constant over time (see also Appendix 5 for additional evidence of heteroscedasticity with the fat tail of the histogram distribution). The null hypothesis is that there is no presence of heteroscedasticity in the returns series. And since the probability value is less than 0.05%, then the null hypothesis is rejected and the alternative hypothesis of presence of ARCH effects or heteroscedasticity is accepted.

4. The linear and non-linear GARCH models

The presence of the ARCH effects in our variables as presented in **Table 3** endorses the use of the GARCH models. There are many types of GARCH models. We have the symmetric (linear) GARCH, which is the normal GARCH and asymmetric (nonlinear) GARCH such as exponential GARCH (EGARCH) and the Threshold GARCH (TGARCH) or Glosten, Jagannathan and Runkle GARCH (GJR-GARCH).

We started with the ARCH model formulated in two parts, the mean equation and the variance equation proposed by Engle [24] and written as:

$$Y_t = \alpha + \beta' X_t + \mu_t \tag{1}$$

Eq.(1) is the mean equation, where Y_t is a column vector of response variables, α is the constant term, β' is a row vector of unknown parameters, X_t is a column vector of explanatory variables and μ_t is a column vector of random error terms with $\mu_t = z_t\sqrt{h_t}$. Where $z_t \approx (0, h_t)$ and h_t is a scaling factor. The variance equation of the ARCH model on the other hand in general term is stated as:

$$h_t = \gamma_0 + \sum_{i=1}^{q} \gamma_i u_{t-i}^2 \tag{2}$$

The limitation of the ARCH model is that it is more of a moving average (MA) model where the variance is only responding to the errors. The autoregressive (AR) parts of the model are not captured, hence the use of more superior model like the GARCH model propounded by Bollerslev [25]. The mean equation still remains the same while the variance equation in general term is written a bit differently from the ARCH model as:

$$h_t = \gamma_0 + \sum_{i=1}^{p} \lambda_i h_{t-i} + \sum_{i=1}^{q} \gamma_i u_{t-i}^2 \tag{3}$$

The GARCH model equally has its own deficiency; it cannot accounts for the impacts of news and events that can have asymmetric effects on financial assets. For instance, investors would react differently to the occurrence of good or bad news to financial assets or the market. Whenever bad news happen in the financial market, the volatility is usually higher and larger than a state of tranquility. To address such asymmetric effects, non-linear or asymmetric GARCH models such as TGARCH and EGARCH are propounded. The TGARCH model propounded by Zokoian [26] can be stated in its general form as:

$$h_t = \gamma_0 + \sum_{i=1}^{p} \lambda_i h_{t-i} + \sum_{i=1}^{q} (\phi_i + \eta_i D_{t-i}) u_{t-i}^2 \tag{4}$$

Where D_{t-i} = 1 is bad news for $u_t < 0$ and 0 otherwise, β_i measures good news, η_i denotes the asymmetry or leverage term, $\eta_i > 0$ implies asymmetry, while $\eta_i = 0$means symmetry. If η_i is found to be significant and positive, then negative shocks have larger impacts on the conditional variance, h_t than the positive shocks. Another asymmetric GARCH model is EGARCH propounded by Nelson [27] described in logarithm form as:

$$\log(h_t) = \gamma_0 + \sum_{i=1}^{p} \beta_i \left| \frac{u_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{i=1}^{q} \gamma_i \frac{u_{t-i}}{\sqrt{h_{t-i}}} + \sum_{i=1}^{m} \alpha_i \log(h_{t-i}) \tag{5}$$

where good news is denoted by positive value of u_{t-i} with total effect as $(1+\gamma_i)|u_{t-i}|$ and bad news given by u_{t-i} being negative with total effect as $(1-\gamma_i)|u_{t-i}|$. If $\gamma_i < 0$ then bad news is assumed to have higher effects on volatility than good news. There is symmetry if $\gamma_i = 0$ and there is asymmetry if $\gamma_i \neq 0$. In short, γ_0 is the constant term, β_i measure the ARCH effect, γ_1 measures the leverage effect and lastly, α_i account for the GARCH effect.

5. Empirical analysis and result discussions

Having described both the symmetric and asymmetric GARCH, we expressed the variables of interest from the mean equation as:

$$RSP_t = \alpha + \beta ROP_t + u_t \tag{6}$$

Eq. (6) expresses stock price return as a function of oil price return. Where RSP_t is the return of the stock price over time, α is the constant term, ROP_t is the returns of the oil price, β is the marginal effect of the oil price on the stock price while u_t is the error term. The variance equation with the parsimonious GARCH (1,1) model is stated as:

$$h_t = \gamma_0 + \lambda_1 h_{t-1} + \gamma_1 u_{t-1}^2 \tag{7}$$

Where $\lambda_1 + \gamma_1 < 1$ implies stationarity and $\lambda_1 + \gamma_1 > 1$ signifies non-stationarity of the ARCH and GARCH. The justification for the choice of GARCH (1,1) apart from being parsimonious is that the variance model depends on the most recent past variance. The use of any higher lags would result to loss of degree of freedom, information and over parameterization of the GARCH model [28]. The GARCH (1,1) model is estimated with different error distributions so as to identify the model with minimum variance using the Schwarz criterion (SC) and the log likelihood. The GARCH model with the minimum variance represents the model with minimum asset risk. The result of the of the GARCH (1,1) model with different error distributions is presented in **Table 4** (See the Appendix 1 for the log likelihood of the distributions). It can be observed from the **Table 4** that all the GARCH (1,1) result with the different errors are stationary given that their parameter values of $\lambda_1 + \gamma_1 < 1$. In addition, the previous period of volatility of all the error distributions have significant effects on the current conditional volatility. For the GARCH (1,1) with normal distribution error, the sum of the coefficients of the ARCH and GARCH [the sum of the residual square and Garch(−1)] are positive and statistically significant at 0.05% with a value of 0.9037. The value is less than 1, which satisfies the stability condition of the GARCH process. That of the[1] student-t error distribution is 0.8473 and 0.8731 for the generalized error distribution model. The result suggests that the persistence of volatility effects of oil price on stock price is large for Nigeria (the volatility clustering in **Figure 2** equally suggests the persistence of volatility movement of the two series). The large volatility for Nigeria is supported by previous study done by Uyaebo et al. [8] done for six selected countries with Nigeria inclusive. For the GARCH (1,1), the error distribution for the student-t error distribution is 0.85%, 0.87% for generalized error distribution, and there is highest value of 0.90% for normal distribution. The mean equation, on the other hand, implies that 1% change in oil price affects the stock price by 0.13% for the GARCH (1,1) using normal distribution and the generalized error distribution while it is a bit higher at 0.14% for student-t error distribution. However, in terms of the model with goodness of fit and with minimum variance, the GARCH (1,1) model with student-t error distribution behaves optimally with minimum SC value of −2.56 and with the highest log likelihood value of 327.18. The implication of the optimality of the student-t error distribution implies that stock price returns in Nigeria is unpredictable and volatile because of the effect of the global oil price. We therefore conclude here that GARCH (1,1) process with student-t error distribution

[1] More exposition on student-t distribution can be found in Fisher (1925).

Dependent variable: stock price				
Normal Dist.				
Mean equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
dlogoilprice	0.1257	0.0265	4.7473	0.00***
Constant	0.0117	0.0046	2.5352	0.01***
Variance equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
Constant	0.0005	0.0003	1.8414	0.07*
residual square	0.1562	0.0699	2.2362	0.03**
Garch(−1)	0.7475	0.101	6.7968	0.00***
Log likelihood	321.37			
Schwarz criterion	−2.53			
Student t dist.				
Mean equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
dlogoilprice	0.1384	0.0324	4.2693	0.00***
Constant	0.0079	0.004	2.013	0.04**
Variance equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
Constant	0.0007	0.0006	1.2456	0.21
Residual square	0.0995	0.0769	1.2943	0.19
Garch(−1)	0.7478	0.174	4.2983	0.00***
Log likelihood	327.18			
Schwarz criterion	−2.56			
Generalized error				
Mean equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
dlogoilprice	0.1286	0.0315	4.0756	0.00***
Constant	0.0084	0.0039	2.1526	0.03**
Variance equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
Constant	0.0006	0.0005	1.3042	0.19
Residual square	0.1230	0.0889	1.3836	0.17
Garch(−1)	0.7501	0.1619	4.6326	0.00***
Log likelihood	326.01			
Schwarz criterion	−2.54			

****, **, * represent significance level at 1, 2, and 10%, respectively.*

Table 4.
GARCH (1,1) results of stock prices and oil prices volatility.

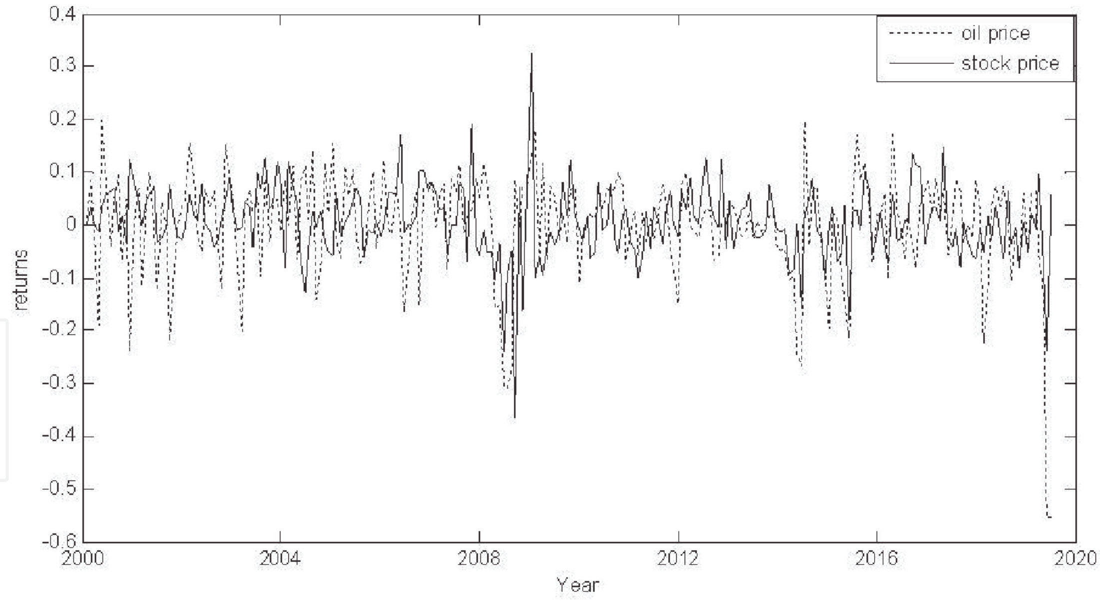


Figure 2.
Graph of the monthly returns of oil price and stock price over the period of study.

is the best selection model for financial investors when taking decisions on the volatility effects of oil price on stock price in Nigeria.

Due to the limitation of the standard ARCH and GARCH model of not capable of capturing news, events and incidents that result in asymmetric impacts on financial assets in financial markets, the use of TGARCH and EGARCH that are more superior in accounting for good and bad news (the asymmetric and non-linear effects) became popular. The GARCH model usually treats the innovation in absolute term with the squared residual. However, with the TGARCH and EGARCH, the residual is decomposed into negative effects $(u_{t-i} < 0)$ and the positive effects $(u_{t-i} > 0)$. The parsimonious TGARCH (1,1) model can be written as: $h_t = \gamma_0 + \lambda_1 h_{t-1} + \gamma_1 u_{t-1}^2 + \alpha_1 u_{t-1}^2 D_{t-1}$ and the result presented in **Table 5** with the error distributions. The marginal effects of oil price on stock price is almost similar with the GARCH (1,1) result with almost 0.13 at 1% significance level for all the error distributions. Also, the GARCH effect is significant at 1% for all the error distributions, suggesting significant effects of past conditional volatility on the current volatility. This implies volatility effects of oil price on stock price in Nigeria. For TGARCH (1,1) model of the normal distribution, we found the positive effect (good news) to be insignificant with coefficient value of 0.02% while that of the negative effect (bad news) is significant at 5% with coefficient value of 0.26% (sum of 0.0176 and 0.2454). The difference between the positive effect and negative effect is 0.2454, which is the leverage effect. The result shows presence of leverage effect and negative effect of oil price has more significant impact on stock prices than positive effect. In the same vein, the positive and negative effects of the TGARCH (1,1) model using the student-t error distribution are 0.0373 and 0.1341, respectively, though the negative effect is not significant like the TGARCH (1,1) normal distribution. The negative effect also has larger effect of 0.13% than the positive effect with 0.04%. This finding supports previous study in Nigeria by Salisu [6] that also found bad news to have large effect than good news in oil market. The TGARCH (1,1) for the generalized error distribution also show asymmetric effect though the negative effect is also not significant. The negative effect has coefficient value of 0.1940 while the positive effect is 0.0276. In overall, similar to the GARCH (1,1) model, the student-t error distribution is also found to have the minimum variance with SC value of −2.54 and the maximum log likelihood value of 327.98. We, therefore, conclude

Dependent variable: stock price				
Normal Dist.				
Mean equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
dlogoilprice	0.1271	0.0293	4.3383	0.00***
Constant	0.0106	0.0045	2.3545	0.02**
Variance equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
Constant	0.0008	0.0004	1.9647	0.05*
Residual square	0.0176	0.0726	0.2424	0.81
resid square(resid(−1) > 0	0.2454	0.123	1.9957	0.04**
Garch(−1)	0.6862	0.1319	5.2028	0.00***
Log likelihood	324.67			
Schwarz criterion	−2.53			
Student t dist.				
Mean equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
dlogoilprice	0.1393	0.0338	4.1172	0.00***
Constant	0.0080	0.0040	2.0086	0.04**
Variance equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
Constant	0.0008	0.0006	1.3834	0.17
Residual square	0.0373	0.0886	0.4214	0.67
Resid square(resid(−1) > 0	0.1341	0.1327	1.0100	0.31
Garch(−1)	0.7111	0.1838	3.8685	0.00***
Log likelihood	327.98			
Schwarz criterion	−2.54			
Generalized Error dist.				
Mean equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
dlogoilprice	0.1305	0.03335	3.8936	0.00***
Constant	0.0082	0.0040	2.0685	0.04**
Variance equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
Constant	0.0008	0.0005	1.4810	0.13
Residual square	0.0276	0.0902	0.3060	0.75
Resid square(resid(−1) > 0	0.1940	0.1496	1.2969	0.19
Garch(−1)	0.6974	0.1766	3.9499	0.00***
Log likelihood	327.62			
Schwarz criterion	−2.53			
****, **, * represent significance level at 1, 2, and 10%, respectively.*				

Table 5.
TGARCH (1,1) results of stock prices and oil prices volatility.

that news, information and events on oil prices are very significant to stock price volatility in Nigeria.

In order to have a robust estimation and result, the EGARCH, another asymmetric or non-linear model, is considered to compare its result with the TGARCH model. The parsimonious EGARCH (1,1) is also specified as: $\log(h_t) = \gamma_0 + \beta_1 \left| \frac{u_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma_1 \frac{u_{t-1}}{\sqrt{h_{t-1}}} + \alpha_1 \log(h_{t-1})$. The result of the EGARCH (1,1) model is presented in **Table 6**. Looking at the mean equation of the EGARCH (1,1) result with the normal distribution, we found oil price to have 0.17% significant effect on stock price in Nigeria at 1% significance level. The ARCH and the leverage term are not significant while the GARCH terms are significant at 10%. For the ARCH term,

Dependent variable: stock price				
Normal dist.				
Mean equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
dlogoilprice	0.1700	0.0285	5.9670	0.00***
Constant	0.0053	0.0050	1.0484	0.29
Variance equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
Constant	−7.8302	1.4262	−5.4903	0.00***
Residual square	0.0112	0.1446	0.0773	0.94
Leverage term	0.1330	0.0850	1.5640	0.12
Garch(−1)	−0.4560	0.2709	−1.6831	0.09*
Log likelihood	307.63			
Schwarz criterion	−2.44			
Student t dist.				
Mean equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
dlogoilprice	0.1375	0.0342	4.0190	0.00***
Constant	0.0091	0.004	2.2437	0.02**
Variance equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
Constant	−1.0114	0.6257	−1.6165	0.11
Residual square	0.2042	0.1322	1.5447	0.12
Leverage term	−0.0567	0.0783	−0.7248	0.47
Garch(−1)	0.8421	0.1064	7.9128	0.00***
Log likelihood	327.20			
Schwarz criterion	−2.53			
Generalized error dist.				
Mean equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
dlogoilprice	0.1257	0.0334	3.7506	0.00***
Constant	0.0090	0.0040	2.2599	0.04**

Dependent variable: stock price				
Variance equation				
Variables	Coefficient	Std. error	z-Statistics	Prob.
Constant	−0.9643	0.5425	−1.7777	0.08*
Residual square	0.2227	0.1404	1.5859	0.11
Leverage term	−0.0838	0.0805	−1.0418	0.30
Garch(−1)	0.8537	0.0914	9.3394	0.00***
Log likelihood	326.65			
Schwarz criterion	−2.53			

****, **, * represent significance level at 1, 2, and 10%, respectively.*

Table 6.
EGARCH (1,1) results of stock prices and oil prices volatility.

the result shows a positive relationship between the shock of the oil price and the volatility of stock price returns. Also, the leverage effect is positive meaning that good news prevails over bad news in the oil market on stock price volatility. Negative effect is found between the past volatility and the future. The past volatility negatively predicts the future volatility at 10% significance level. We further examine the EGARCH (1,1) result with the student-t distribution and we found the marginal effect of oil price on stock price returns to be 0.14%, lower than the 0.17% of the EGARCH (1,1) model with normal distribution. Similar to the result of the normal distribution, the ARCH and the leverage term are also not significant only the GARCH term is significant at 1%. The ARCH term shows a positive relationship between the oil price shocks and the stock price volatility returns. 1% increase in oil price shock, stock price fluctuates by 0.20%. The leverage effects on the other hand are negative. This implies that 1% increase in the negative shocks in the oil price; it reduces the stock price returns by 0.06%. The GARCH term is significant at 1% level suggesting that the previous volatility predicts significantly the future volatility in the effect of oil price volatility on stock price returns. A 1% increase in past volatility leads to 0.84% increase in future volatility significantly at 1% level. Lastly, we examine the EGARCH (1,1) result using the generalized error distribution and we found the marginal effect of oil price volatility on stock price returns to be 0.13% at 1% significance level. The result of the ARCH, leverage and GARCH term of the generalized error term is similar to that of the student-t distribution. The ARCH term shows that 1% increase in the oil price shock insignificantly increases the stock price returns by 0.22%. The leverage effect also shows prevalence of bad news with 1% increase in bad news in the oil market reducing stock price returns by 0.08%. The GARCH term is significant with 0.85% future volatility increase resulting from 1% increase in past volatility in relation to the effect of oil price on the stock price in Nigeria. Of all the distributions, the EGARCH (1,1) of the student-t distribution is found to be the best model with minimum variance looking at the SC and likelihood. The EGARCH (1,1) with student-t distribution has SC with minimum value of −2.53 and likelihood maximum value of 327.20. We therefore conclude that both the standard GARCH and non-linear GARCH process driven by the student-t distribution is the best selection model for investors for valuing the volatility effect of oil price on stock price in Nigeria. Finally, considering the diagnostic tests of our model, the serial correlation for all the error distributions used are presented at the

Appendix 4 showing rejection of the null hypothesis of presence of serial correlation with p-values greater than 0.05.

6. Conclusion and policy implications

In this study we examined the volatility effects of oil price behavior on stock price in Nigeria from the first month of year 2000 to the fourth month of year 2020 using both standard and asymmetric GARCH. Before performing the GARCH, TGARCH and EGARCH, we carried out some preliminary tests such as the ARCH tests for heteroscedasticity, unit root test for stationary test and all the tests show evidence of volatility clustering which necessitate the use of GARCH process on the variables. The standard GARCH was first done and the model with student-t distribution showed goodness of fit. We proceeded to use the non-linear GARCH models such as the TGARCH and EGARCH to account for news, events and information that can filter into the oil market and thereby create asymmetric behavior in the financial market. The non-linear GARCH models also confirm the student-t distribution as the best model for traders in the financial market in Nigeria. In this study, we found oil price volatility to be a significant predictor of stock price returns. Secondly, our study showed that the volatility movement is high and persist over the study period. Also, we found leverage effects in stock price response to oil price. Bad news tends to increase volatility than good news. One of the implications of the findings of this study is that oil price volatility should be considered in the prediction of stock price returns by investors and financial analyst in Nigeria. In addition, the finding implies that most of the investors in the financial market are risk averse; this is because they are more sensitive in their asset decisions to bad news than to good news. This study concludes that bad news have much effects on investors than good news in the movement of oil price effect to stock price returns.

A. Appendix

A.1 The probability density function of normal distribution is written as:

$$f(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{8}$$

and its log likelihood function in GARCH term is:

$$-\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(h) - \frac{1}{2h}\sum_{j=1}^{n}\left(x_j - \mu\right)^2. \tag{9}$$

A.2 The probability density function of the student-t distribution is:

$$f(y,\nu) = \frac{\Gamma\frac{\nu+1}{2}}{\sqrt{\pi(\nu-2)}\Gamma\frac{\nu}{2}\left(1+\frac{\nu^2}{\nu-2}\right)^{\frac{\nu+1}{2}}} \tag{10}$$

Its log likelihood function in GARCH term is:

$$\log\left[\Gamma\left(\frac{\nu+1}{2}\right)\right] - \log\left[\Gamma\left(\frac{\nu}{2}\right)\right] - \frac{1}{2}\log\left(\pi(\nu-2)\right) - \frac{1}{2}\sum_{j=1}^{n}\left[\log\left(h_t\right) + (\nu+1)\log\left(1+\frac{\varepsilon_t^2}{h_t(\nu-2)}\right)\right] \tag{11}$$

A.3 The probability density function of the generalized error distribution is:

$$f(x|\mu, \sigma, \kappa) = \frac{e^{-\frac{1}{2}|x-\mu|^{\frac{1}{n}}}}{2^{\kappa+1}\sigma\Gamma(\kappa+1)} \tag{12}$$

Its log likelihood function in GARCH term is:

$$-\frac{1}{2}|x-\mu|^{\frac{1}{n}} - (\kappa+1)\log(2) - \log(h) - \log(\Gamma) - \log(\kappa+1) \tag{13}$$

A.4 Diagnostic test of student's t for serial correlation

Date: 05/12/20 Time: 00:06						
Sample: 2000:01 2020:12						
Included observations: 243						
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	−0.028	−0.028	0.1887	0.664
.|. |	.|. |	2	−0.025	−0.025	0.3376	0.845
.|* |	.|* |	3	0.107	0.106	3.1875	0.364
.|. |	.|. |	4	0.040	0.045	3.5767	0.466
.|. |	.|. |	5	0.024	0.031	3.7163	0.591
.|. |	.|. |	6	−0.002	−0.010	3.7169	0.715
.|. |	.|. |	7	0.039	0.032	4.1050	0.768
.|. |	.|. |	8	0.014	0.009	4.1571	0.843
.|. |	.|. |	9	−0.054	−0.054	4.9051	0.842
.|. |	.|. |	10	−0.024	−0.036	5.0550	0.887
.|* |	.|* |	11	0.101	0.093	7.6682	0.743
.|. |	.|. |	12	0.023	0.038	7.8105	0.800
.|. |	.|. |	13	−0.051	−0.036	8.4859	0.811
.|. |	.|. |	14	−0.039	−0.059	8.8732	0.839
.|. |	.|. |	15	−0.035	−0.054	9.1869	0.868
.|. |	.|. |	16	−0.062	−0.063	10.192	0.856
.|. |	.|. |	17	0.004	0.014	10.195	0.895
.|. |	.|. |	18	0.004	0.010	10.199	0.925
.|. |	.|. |	19	−0.039	−0.025	10.601	0.937
.|. |	.|. |	20	−0.038	−0.023	10.977	0.947
.|. |	.|. |	21	−0.023	−0.014	11.121	0.960
.|. |	.|. |	22	−0.040	−0.048	11.545	0.966
.|. |	.|. |	23	−0.050	−0.057	12.227	0.967
.|* |	.|* |	24	0.136	0.146	17.252	0.838
.|. |	.|. |	25	−0.052	−0.028	17.992	0.843
.|. |	.|* |	26	0.059	0.092	18.936	0.839
*|. |	*|. |	27	−0.069	−0.083	20.253	0.820

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	28	-0.028	-0.038	20.471	0.847
.|* |	.|* |	29	0.157	0.126	27.294	0.556
.|. |	.|. |	30	−0.024	−0.004	27.457	0.599
.|. |	.|. |	31	0.046	0.058	28.054	0.618
.|. |	.|. |	32	−0.013	−0.045	28.101	0.664
.|. |	.|. |	33	0.013	0.022	28.145	0.708
.|. |	.|. |	34	0.054	0.053	28.981	0.712
*|. |	*|. |	35	−0.069	−0.106	30.354	0.692
.|. |	.|. |	36	−0.003	−0.036	30.357	0.734

* no serial correlation since p-values >0.05%.

Diagnostic test of Normal distribution for serial correlation

Date: 05/12/20 Time: 00:08

Sample: 2000:01 2020:12

Included observations: 243

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	−0.014	−0.014	0.0483	0.826
.|. |	.|. |	2	−0.041	−0.041	0.4578	0.795
.|. |	.|. |	3	0.069	0.068	1.6444	0.649
.|. |	.|. |	4	0.005	0.005	1.6495	0.800
.|. |	.|. |	5	0.031	0.036	1.8822	0.865
.|. |	.|. |	6	0.017	0.014	1.9549	0.924
.|. |	.|. |	7	0.035	0.037	2.2564	0.944
.|. |	.|. |	8	0.008	0.006	2.2729	0.971
.|. |	.|. |	9	−0.052	−0.052	2.9643	0.966
.|. |	.|. |	10	−0.034	−0.041	3.2544	0.975
.|. |	.|. |	11	0.066	0.059	4.3691	0.958
.|. |	.|. |	12	0.033	0.037	4.6579	0.968
*|. |	.|. |	13	−0.068	−0.059	5.8644	0.951
.|. |	.|. |	14	−0.053	−0.060	6.5925	0.949
.|. |	.|. |	15	−0.048	−0.057	7.1937	0.952
*|. |	*|. |	16	−0.074	−0.072	8.6166	0.928
.|. |	.|. |	17	0.021	0.022	8.7326	0.948
.|. |	.|. |	18	0.012	0.013	8.7734	0.965
.|. |	.|. |	19	−0.038	−0.027	9.1536	0.971
.|. |	.|. |	20	−0.043	−0.032	9.6408	0.974
.|. |	.|. |	21	−0.024	−0.011	9.7969	0.981
.|. |	.|. |	22	−0.036	−0.039	10.139	0.985

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	*|. |	23	−0.060	−0.070	11.101	0.982
.|* |	.|* |	24	0.152	0.155	17.408	0.831
.|. |	.|. |	25	−0.047	−0.039	18.003	0.842
.|* |	.|* |	26	0.076	0.110	19.586	0.811
*|. |	*|. |	27	−0.085	−0.102	21.580	0.758
.|. |	.|. |	28	−0.037	−0.030	21.949	0.784
.|* |	.|* |	29	0.173	0.133	30.315	0.398
.|. |	.|. |	30	−0.013	−0.008	30.366	0.447
.|. |	.|* |	31	0.060	0.074	31.367	0.448
.|. |	.|. |	32	−0.012	−0.047	31.407	0.496
.|. |	.|. |	33	0.017	0.039	31.486	0.543
.|* |	.|. |	34	0.075	0.072	33.071	0.513
*|. |	*|. |	35	−0.084	−0.121	35.098	0.464
.|. |	.|. |	36	0.015	−0.014	35.160	0.508
* no serial correlation since p-values >0.05%						

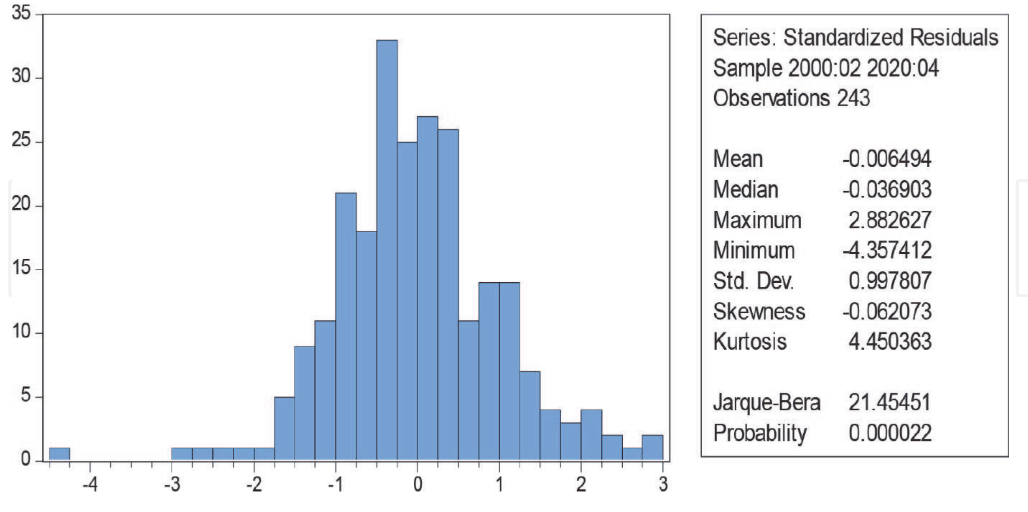
Diagnostic test of Generalised error distribution for serial correlation

Date: 05/12/20 Time: 00:10						
Sample: 2000:01 2020:12						
Included observations: 243						
Autocorrelation	**Partial Correlation**		**AC**	**PAC**	**Q-Stat**	**Prob***
.|. |	.|. |	1	−0.022	−0.022	0.1171	0.732
.|. |	.|. |	2	−0.034	−0.035	0.4108	0.814
.|* |	.|* |	3	0.084	0.083	2.1762	0.537
.|. |	.|. |	4	0.018	0.021	2.2581	0.688
.|. |	.|. |	5	0.025	0.031	2.4107	0.790
.|. |	.|. |	6	0.007	0.003	2.4232	0.877
.|. |	.|. |	7	0.034	0.033	2.7153	0.910
.|. |	.|. |	8	0.015	0.012	2.7737	0.948
.|. |	.|. |	9	−0.057	−0.056	3.5908	0.936
.|. |	.|. |	10	−0.028	−0.037	3.7903	0.956
.|* |	.|* |	11	0.084	0.076	5.6165	0.898
.|. |	.|. |	12	0.025	0.034	5.7782	0.927
.|. |	.|. |	13	−0.060	−0.049	6.7146	0.916
.|. |	.|. |	14	−0.047	−0.060	7.2915	0.923
.|. |	.|. |	15	−0.042	−0.055	7.7527	0.933
*|. |	*|. |	16	−0.067	−0.066	8.9174	0.917
.|. |	.|. |	17	0.011	0.016	8.9485	0.942
.|. |	.|. |	18	0.012	0.014	8.9844	0.960

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	19	−0.041	−0.030	9.4252	0.966
.|. |	.|. |	20	−0.039	−0.027	9.8406	0.971
.|. |	.|. |	21	−0.024	−0.015	10.000	0.979
.|. |	.|. |	22	−0.040	−0.046	10.438	0.982
.|. |	.|. |	23	−0.056	−0.065	11.286	0.980
.|* |	.|* |	24	0.148	0.155	17.255	0.838
.|. |	.|. |	25	−0.051	−0.036	17.956	0.844
.|. |	.|* |	26	0.068	0.102	19.242	0.826
*|. |	*|. |	27	−0.076	−0.091	20.830	0.794
.|. |	.|. |	28	−0.030	−0.031	21.072	0.822
.|* |	.|* |	29	0.163	0.127	28.470	0.493
.|. |	.|. |	30	−0.019	−0.006	28.572	0.540
.|. |	.|. |	31	0.051	0.064	29.312	0.553
.|. |	.|. |	32	−0.010	−0.046	29.343	0.602
.|. |	.|. |	33	0.016	0.035	29.417	0.646
.|. |	.|. |	34	0.067	0.065	30.701	0.630
*|. |	*|. |	35	−0.077	−0.113	32.379	0.595
.|. |	.|. |	36	0.009	−0.021	32.402	0.640

*no serial correlation since p-values >0.05%

A.5 The presence of fat tail confirm heteroscedasticity of the GARCH process



Conflict of interest

The author declares no conflict of interest.

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